

# Predicting Post Fire Cheatgrass Invasion

## Dinosaur National Monument

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## Abstract/Introduction

How an invasive species will react to a disturbance events is often difficult to predict. In this study we developed a Post Fire Cheatgrass Abundance Prediction Model to help park managers better understand cheatgrass (*Bromus tectorum*) response to fire events across the Dinosaur National Monument (DINO) landscape.

Using cheatgrass abundance estimates and biogeophysical, disturbance history, climatic and fire properties geospatial explanatory variables, modeling was performed in a two step process. First classification tree modeling was performed to identify significant explanatory variables. Next Boosted Regression Tree (BRT) modeling was used to develop the final predictive models for three sets of cheatgrass abundance cover levels: Presence/Absence, >10% cover, and >40% cover.

Modeling results had predictive accuracy from a low 0.79 for the presence/absence model, to a high of 0.94 for the >40% cover model. The deterministic variable elevation was found to be the most influential explanatory variable, followed by the contingent fire intensity and post fire precipitation variables.

Lastly four different fire severity and post fire precipitation scenarios were spatially modeled in order to evaluate the influence of the contingent, fire intensity and post fire precipitation variables on cheatgrass distribution and abundance across DINO.

## Methods

### DINO Inventory & Monitoring Data Sources:

Cheatgrass abundance estimates were obtained from vegetation plots collected for vegetation classification at DINO between 2003 through 2005 (Coles et. al. 2008). Fire events across the landscape were obtained from the DINO GIS Fire database, which consists of fire polygons which were digitized from DINO hard copy fire atlas maps. The fire archive consists of fires which have been documented from 1943 – the present. Using vegetation points which were spatially coincident with fire events and collected post fire resulted in the use of 354 vegetation samples, which were associated with 33 fire events (Figure 1).

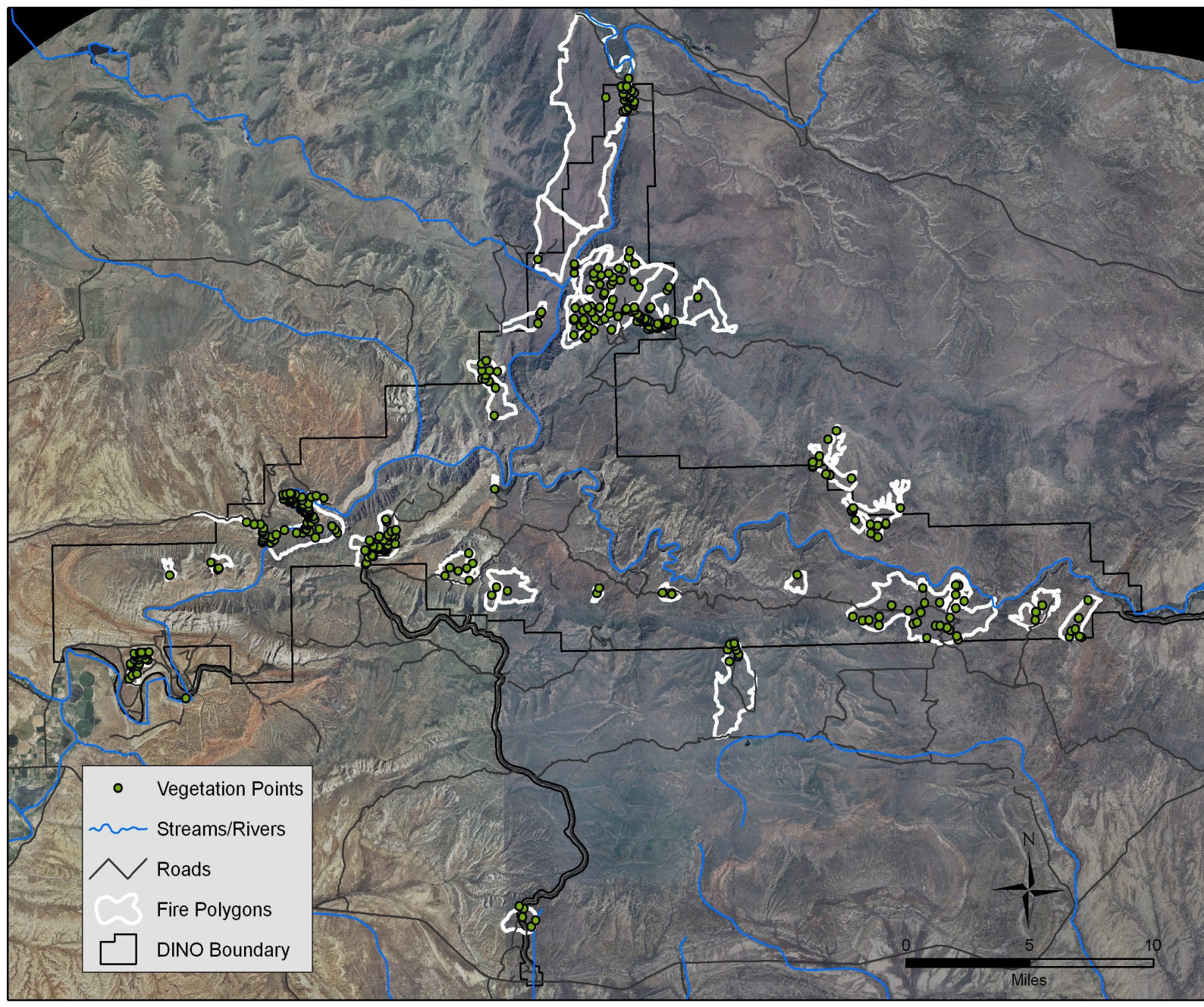


Figure 1. Dinosaur National Monument in NW Colorado, Fire Polygons and Vegetation Points used in analysis.

### Classification Tree - Variable Reduction

Traditional classification trees were used to perform a variable reduction process in order to identify significant explanatory variables in five geospatial modeling groups. The five modeling groups consisted of Biogeophysical, Disturbance History/Sources, Climatic, Fire Properties, and Data Quality related variables. Classification tree analysis was performed in R, using the tree package. After removal of highly correlated and superfluous variables the final set of significant variables to be used in subsequent modeling was identified (Table 1).

Table 1. Significant Explanatory Variables Post Variable Reduction.

Model Group / Variable	Description
<b>Biogeophysical</b>	
ELEV	Elevation
<b>Climatic</b>	
WET_YR1	TasselCap (Wetness) By 1 Year Post Fire 150 Meter Buffer Mean Values
<b>Fire Properties</b>	
dNBR_CONT	delta Normalized Burn Ratio per fire (i.e. landsat scenes used differ by fire and fire date). (dNBR = NBRPostfire - NBR Prefire) . NBR = (NIR - SWIR)/(NIR+SWIR)
<b>Data Quality</b>	
YEARSINCE	Years since last fire
WPPT_YR0	PRISM Winter Precipitation (Dec-April) year of vegetation survey (2002, 2003, 2005)



Whirlpool Canyon

### Boosted Regression Tree Modeling

Using the significant explanatory variables (Table 1), three categorical cheatgrass cover sets (Table 2) were modeled in a Bernoulli fashion (Binary) using Boosted Regression Tree (BRT) modeling. BRT modeling was performed to evaluate ecological relations of post fire cheatgrass abundance with the evaluated explanatory variables and to predict post fire cheatgrass abundance. BRT model training was performed using 254 randomly selected vegetation plots, while 100 randomly selected plots were set aside to test predictive ability. BRT modeling was performed in R using the GBM package and BRT functions written by Elith and Leathwick (2008).



Sphix Moth and Dinosaur Milkweed

Table 2. BRT categorical sets and classification values.

Model/Value	Categorical Set		
	Presence/Absence	10%	40%
1	Present	≥10% Cover	≥40% Cover
0	Absent	<10% Cover	<40% Cover

## Results

### Predictive Ability - Accuracy Assessment

Using the set aside 100 accuracy assessment points, error matrices were used to test the predictive performance of the accuracy assessment models, thus allowing for calculation of overall accuracy, Cohen's kappa and users and producers accuracies by categorical class (Table 3). Overall predictive accuracy for the best models range from a low of 0.79 for the "P/A" model to a high of 0.94 for the "40%" model.

Table 3. Error matrix accuracy assessment plots for the "P/A", "10%" and "40%" best models.

Model/Set	Observed		Total	Users	Overall Accuracy	Cohen's Accuracy
	0 Abs	1 Pres				
Set3	45	0	53	0.85	0.79	0.58
0 Abs	13	44	47	0.72		
1 Pres	58	42				
Producers	0.78	0.81				
Set2	0	1 (≥				
		(-10%) 10%)				
0 (<10%)	72	4	76	0.95	0.89	0.68
1 (≥10%)	7	17	24	0.71		
Total	79	21				
Producers	0.91	0.81				
Set1	0	1 (≥				
		(-40%) 40%)				
0 (<40%)	87	4	91	0.96	0.94	0.67
1 (≥40%)	2	7	9	0.78		
Total	89	11				
Producers	0.98	0.64				



Post Fire Cheatgrass Invasion

Table 4. Relative influence (Friedman and Meulman 2003) of variables by BRT cover class.

Explanatory Variable	Relative Influence By Model Set		
	P/A	≥ 10%	≥ 40%
ELEV	44.2	60.5	57.3
dNBR_CONT	18.7	11.3	26.4
WET_YR1	13.8	12.9	9.6
WPPT_YR0	12.0	6.9	4.4
YEARSINCE	11.3	8.4	2.3

### Relative Contributions

To determine variable influence by model category, the relative influence of explanatory variables was measured using a technique developed by Friedman and Meulman 2003. Across the "P/A", "10%" and "40%" models the biophysical elevation variable is the most influential variable (44, 61, 57) (Table 4). The fire property fire intensity (dNBR\_CONT) (19, 11, 26) and post fire precipitation (WET\_YR1) (14, 13, 10) are the second and third most influential variables.

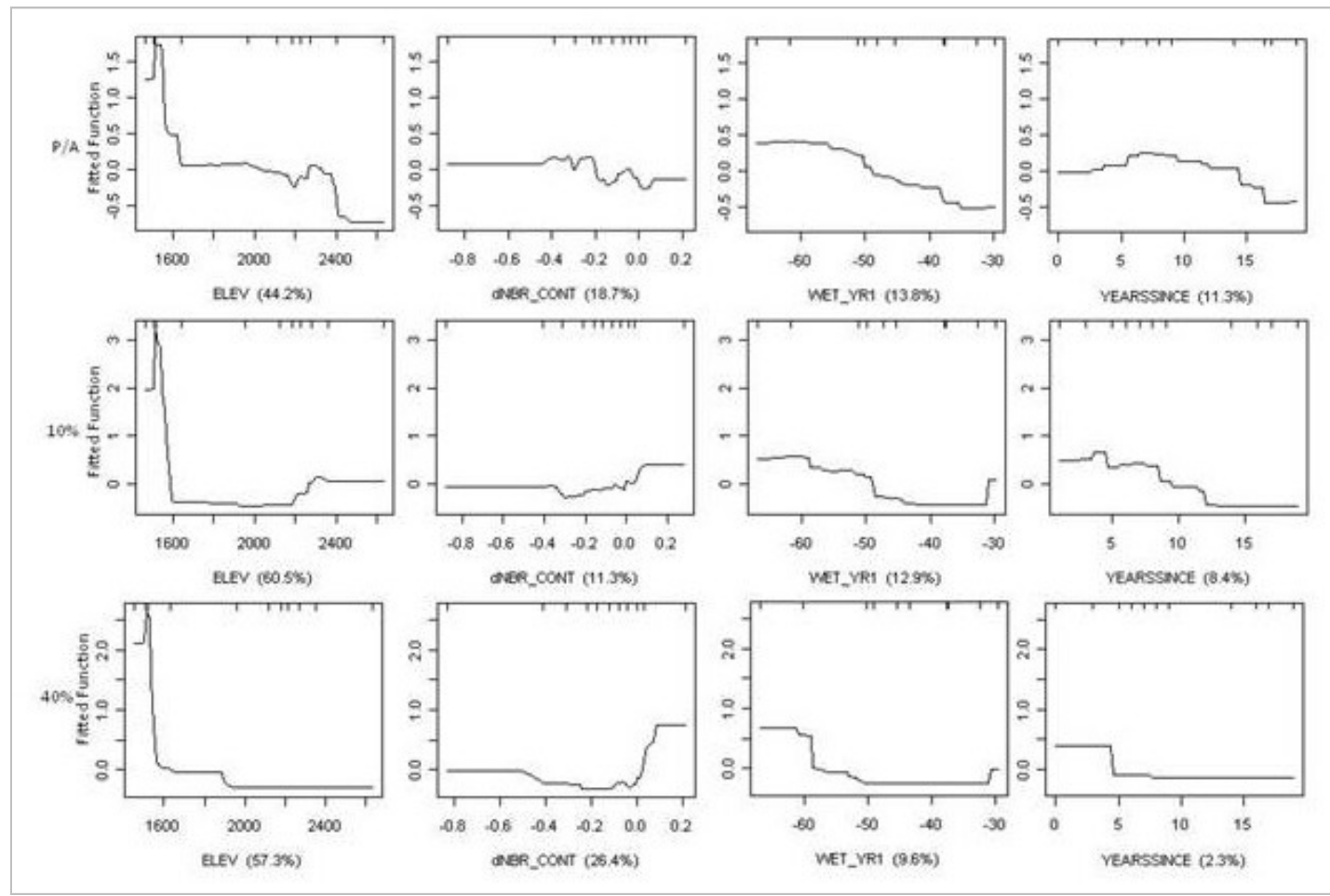


Figure 2. Partial Dependence functions by "P/A", "10%", and "40%" models for the ELEV, dNBR\_CONT, WET\_YR1 and YEARSINCE variables.



Steamboat Rock from Happers Corner Trail.

### Partial Dependence Functions

To further evaluate the relationship between the explanatory variables and the cover class responses, partial dependence plots were made (figure 2). Partial dependence functions show the effect of a variable on the response after accounting for effects from the other explanatory variables in the model. Partial function results show that higher cover levels (i.e. ≥10% and ≥40) have a higher probability of occurrence primarily below 1,600 meters (~5,000 ft). Nevertheless, trace (P/A) levels of cheatgrass have a higher probability up to an elevation of 2,400 meters (~7,800 ft).

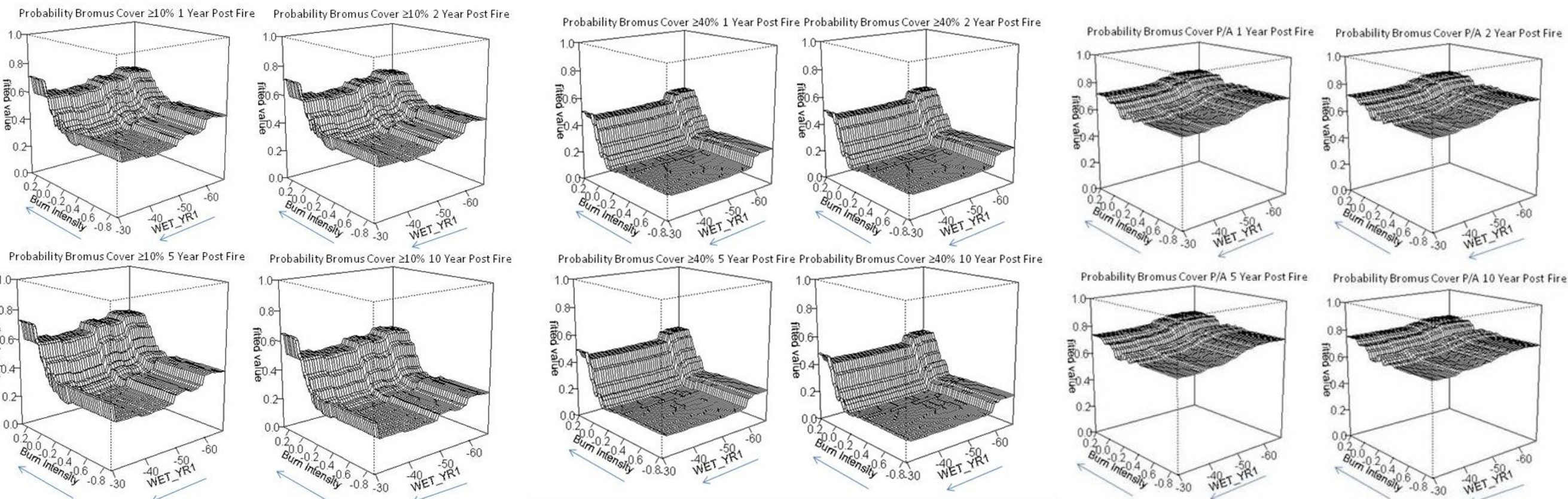


Figure 3. Three - dimensional partial dependence plots for the "10%", "40%", and "P/A" BRT models at an elevation of 1,460 meters at 1, 2, 5, and 10 years post fire. X axis is burn intensity (dNBR\_CONT), y axis is post fire precipitation (WET\_YR1), and the z axis is the BRT model fitted probability of occurrence.

### Three Dimensional Plots - Time Since Fire

To further evaluate complex variable dynamics, three dimensional plots of cheatgrass abundance (per cover category) by varying burn intensities and post fire precipitation values were developed at 1, 2, 5, and 10 year post fire values (Figure 3). In the "10%" plots, as with the partial dependence plots, increased burn intensity and decreased post fire wetness yields higher probability of cheatgrass occurrence. With increasing time from disturbance the influence of fire severity increases as highlighted by the greater slope at higher burn intensity values in the 5, and 10 year plots. The effect of post fire wetness is reduced at higher cheat grass levels (40%), relative to the 10% cover, and time since fire doesn't change the relationship between the cover response and the fire intensity explanatory variables. Lastly, the nearly level P/A plots suggest that at trace level of cheatgrass the burn intensity, wetness and years since fire variables have only a small influence on post fire cheatgrass abundance.

## Fire Severity and Precipitation Scenarios

Modeling results emphasized the importance of the deterministic variable elevation, and the two contingent variables fire intensity (dNBR\_CONT) and post fire precipitation (WET\_YR1) (See Tables 1 & 4 and Results). To better understand the influence the contingent variables have on cheatgrass distribution and abundances across the DINO landscape, we spatially applied BRT models for four different scenarios.

Per cheatgrass category (P/A, 10%, and 40%) we applied the best BRT models using 10% and 90% values for the fire intensity and post fire precipitation variables, while using the true elevation values, a 50% value for the "wppt\_yr0" variable and a 1 year post fire value for the "yearsince" variable. This yielded four scenarios: (1) High Fire Severity/Dry Post Fire (High/Dry), (2) High Fire Severity/Wet Post Fire (High/Wet), (3) Low Fire Severity/Dry Post Fire (Low/Dry), and (4) Low Fire Severity/Wet Post Fire (Low/Wet) (Figures 4-7).

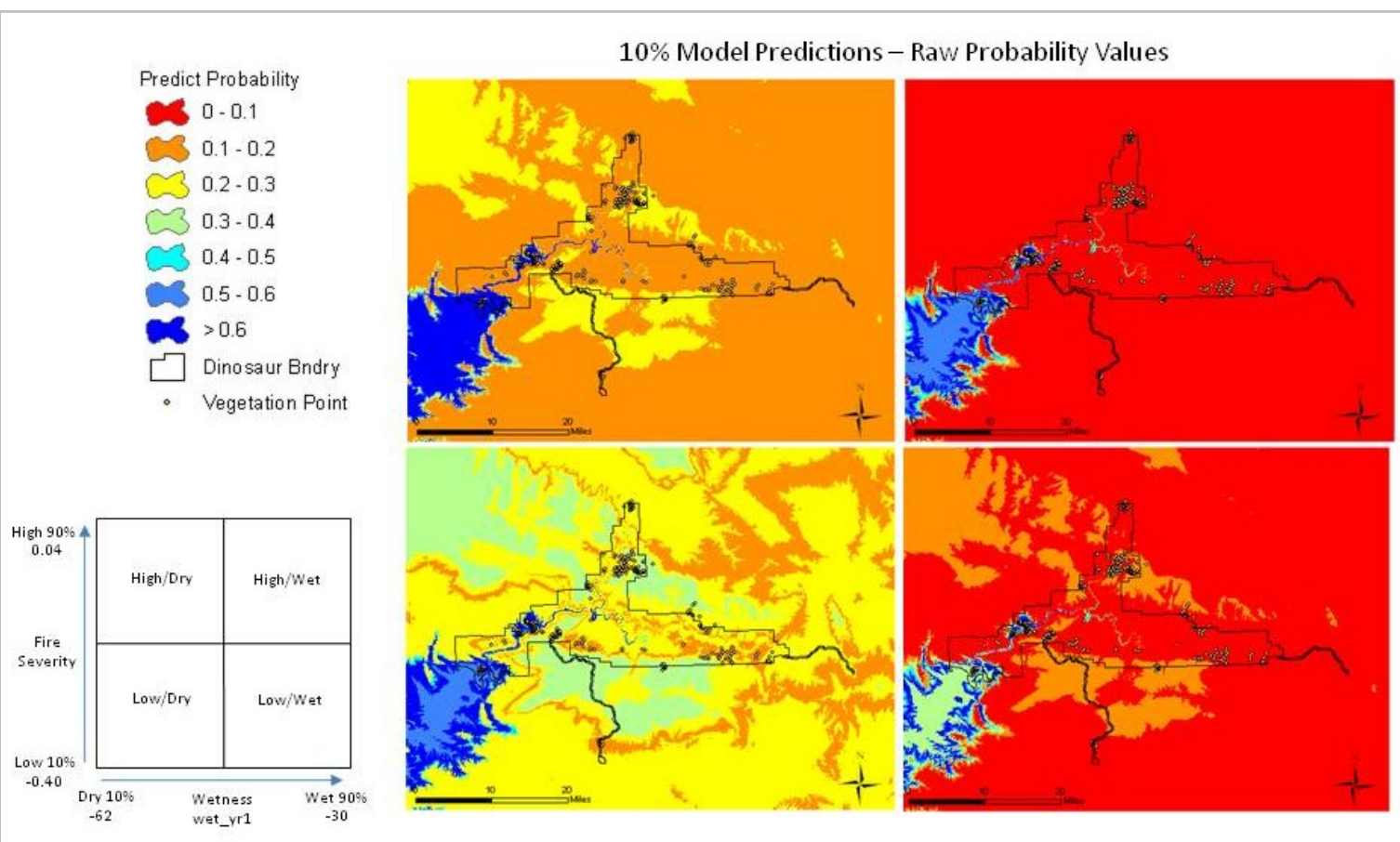


Figure 4. Raw probability output for the 10% spatial scenarios.

When using a Bernoulli model, BRT output is the probability of a positive value (i.e. 1). Raw probability output for the 10% model is shown in Figure 4. Rather than use a traditional split of .5, by model set, a cross validation procedure was performed to find the probability threshold giving the highest number of correctly predicted values in the training set. Applying these threshold values gives explicit classifications per category per scenario (Figures 5-7).

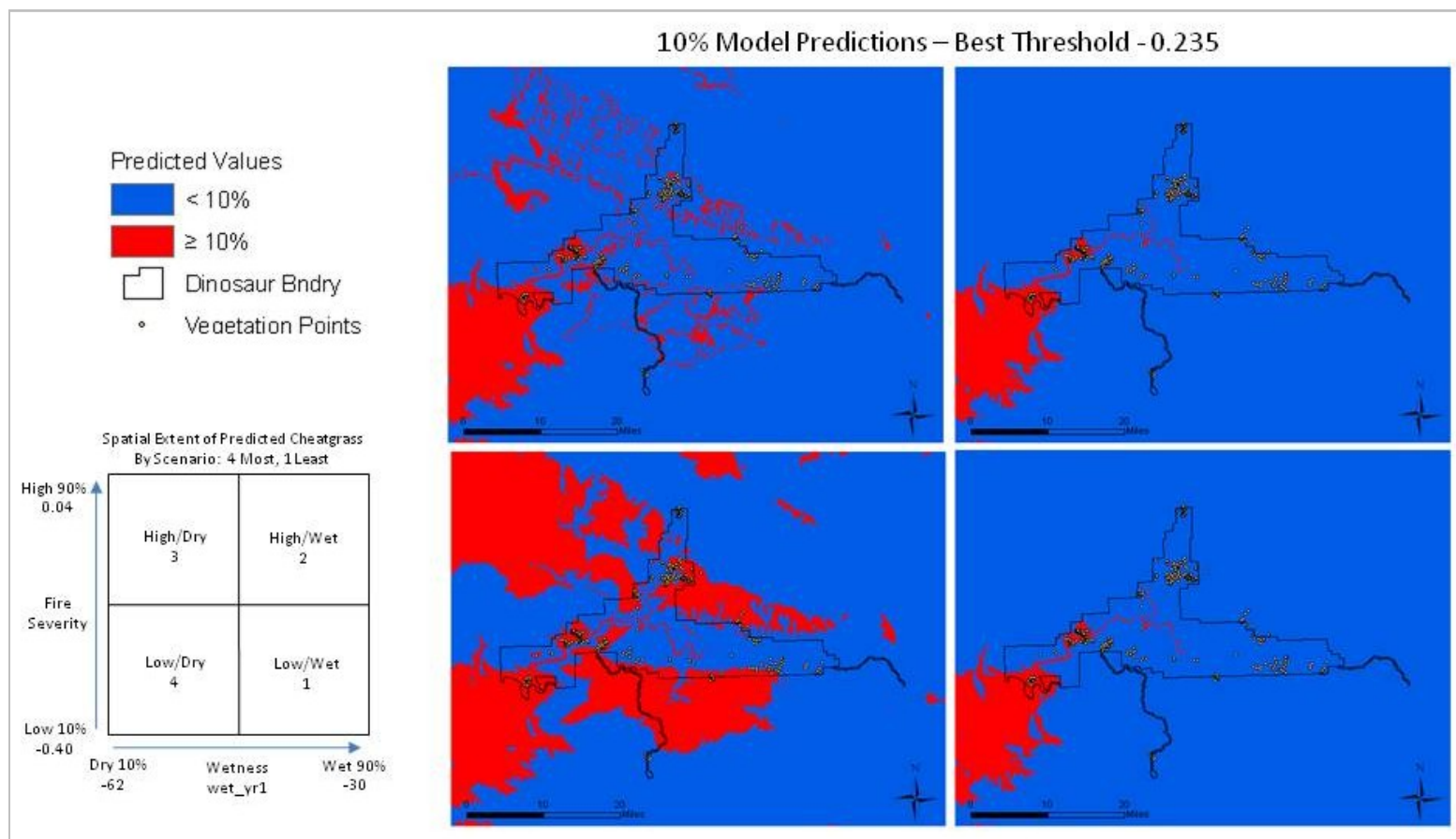


Figure 5. Classifications for the 10% cheatgrass cover scenarios.



Ute Lady's Tresses

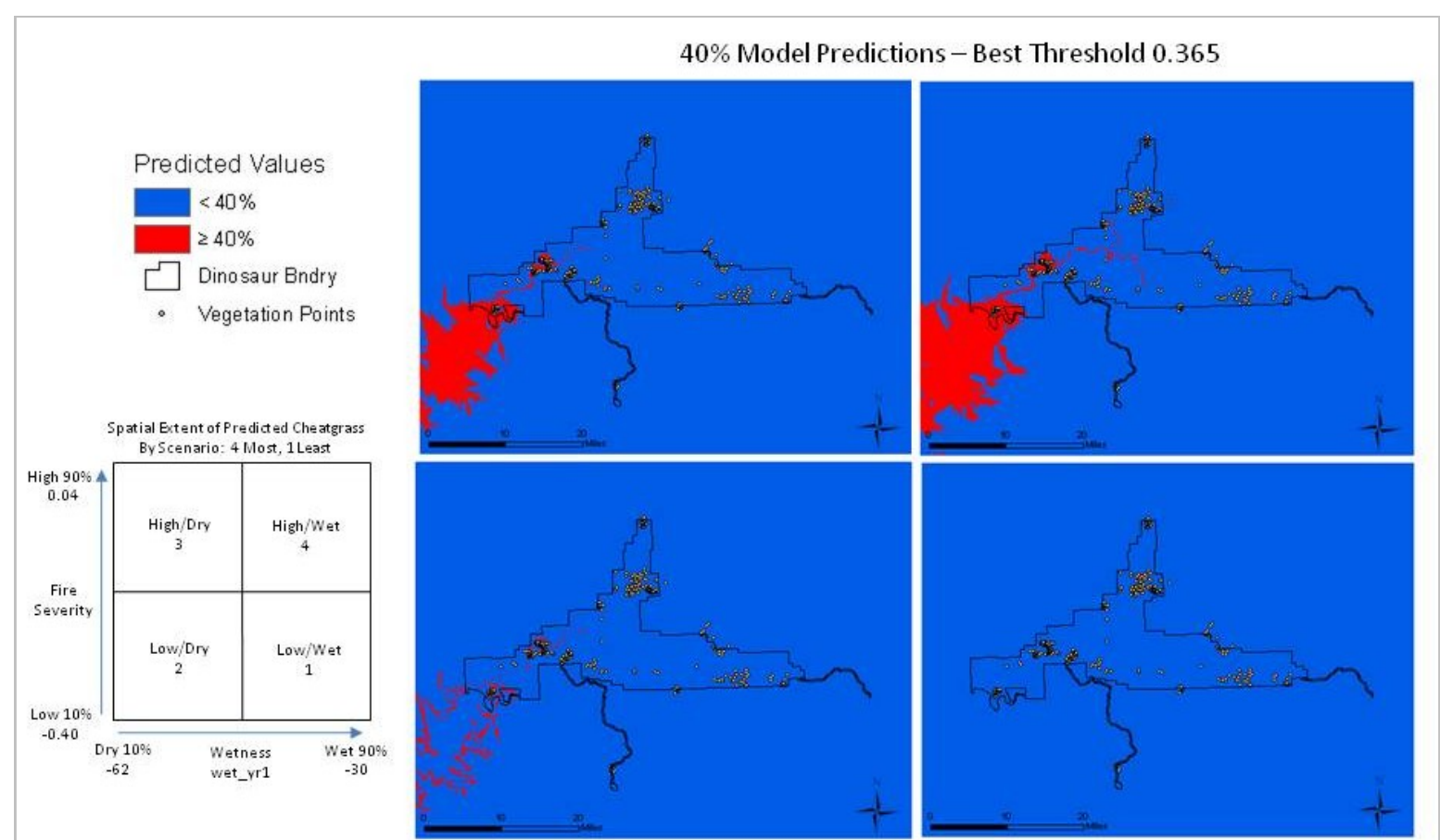


Figure 6. Classifications for the 40% cheatgrass cover scenarios.



Big Horn Sheep on Green River

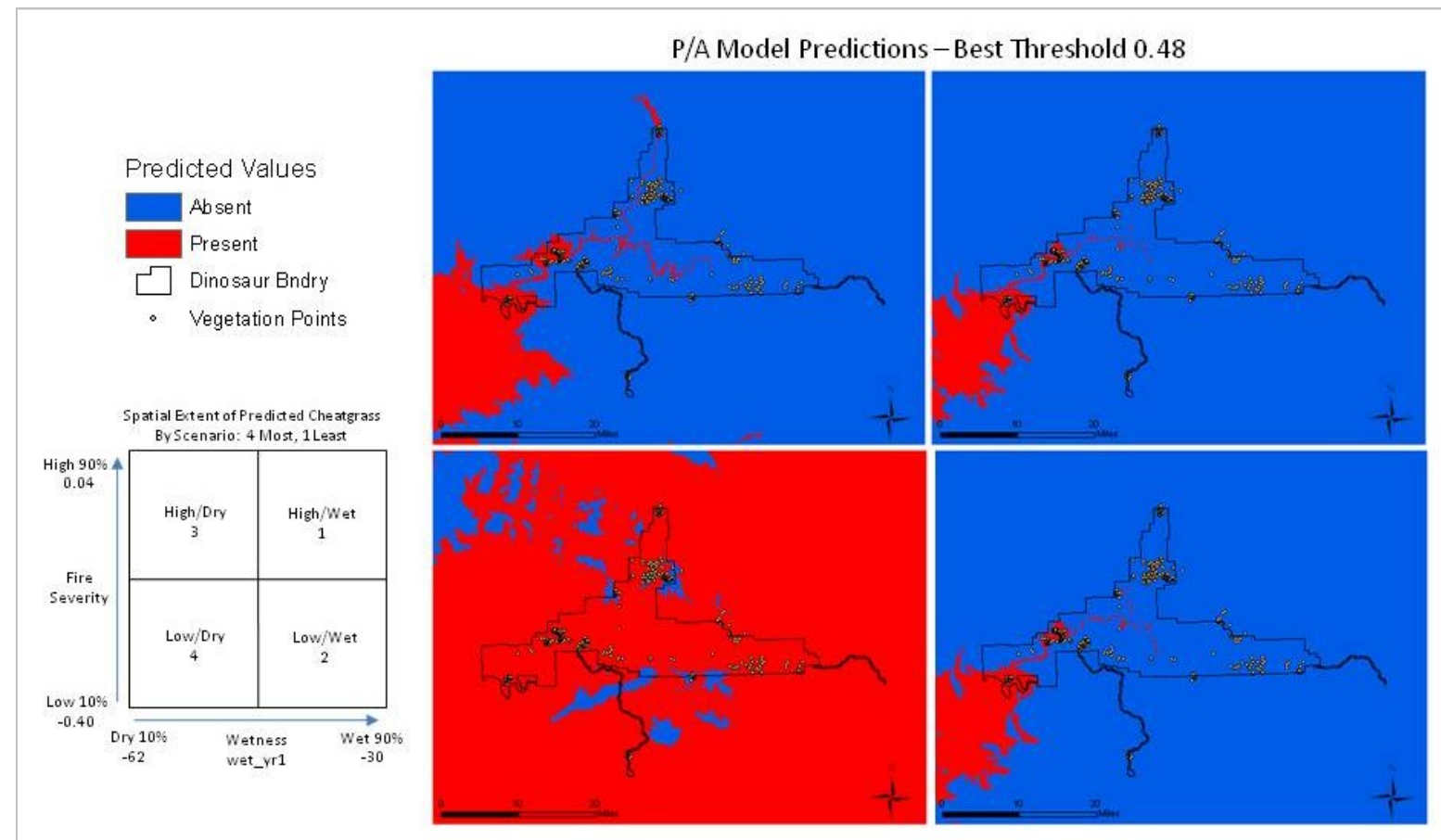


Figure 7. Classifications for the Presence/Absence cheatgrass cover scenarios.



Gates of Lodore

Post fire cheatgrass abundance trends can be gleaned from these scenarios. For example Figure 5 results show that a low intensity fire with dry post fire conditions (Low/Dry) would be most conducive for 10% cheatgrass across the Dino landscape. Conversely the Low/Dry scenario is substantially less likely to facilitate very high levels of cheatgrass as estimated in the 40% model (Figure 6). Interestingly, in the P/A model the Low/Dry scenario estimated a presence of cheatgrass throughout nearly the whole DINO landscape.

## Works Cited

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- Photos courtesy of Peter Williams - Biologist Dinosaur National Monument